University of Waterloo

SD 372 Pattern Recognition

Winter 2003

Lab 3: Image Classification
Due Tuesday, April 1, 2003

1 Overview

This lab will provide experience on working with a real world data set. Image classification is done on a set of texture images using both labelled classification (MICD) and unlabelled clustering (K-means).

Texture analysis is an important aspect of computer vision. Examples include interpretation of remotely sensed images, determining depth cues from scenes, and identification of pertinent objects in medical imaging. In order to assist theoretical development and to be able to compare results from different studies, a standard set of texture images, the Brodatz images, is commonly used in research literature.

The files that are required for this lab can be found on the course homepage collected in a ZIP file. The necessary Matlab scripts for this lab are also included in this file.

There are ten image files (*.im). You can read and view them into Matlab using the commands:

```
image = readim('cloth.im') ;
imagesc(image) ;
colormap(gray) ;
```

The images also appear on the course homepage.

2 Feature Analysis

Each image is either 256×256 or 256×128 pixels in size. We will select sixteen $n \times n$ blocks from each image. Let $d_{ij}(\alpha, \beta)$ be the gray level value of pixel (α, β) in the j^{th} block of the i^{th} image. We propose two features which measure the variability of each image in the horizontal and vertical directions:

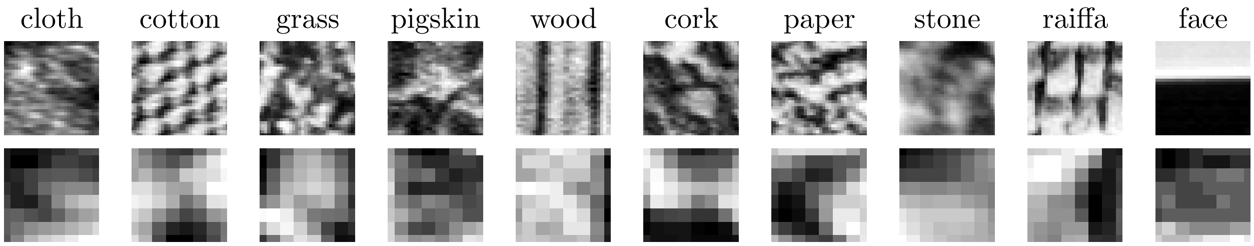

Figure 1: Sample image blocks from which features are derived. The top row consists of 32×32 blocks and the bottom row 8×8 blocks for each texture respectively. Clearly the textures are much harder to discriminate by eye based on the smaller 8×8 feature blocks, so we would expect a classifier trained from these features to have a poorer performance.

$$\underline{x}_{ij} = \begin{bmatrix} \sum_{\alpha=1}^{n} \sum_{\beta=1}^{n-1} \left(d_{ij}(\alpha,\beta) - d_{ij}(\alpha,\beta+1)\right)^2 / ((n)(n-1)) \\ \sum_{\alpha=1}^{n-1} \sum_{\beta=1}^{n} \left(d_{ij}(\alpha,\beta) - d_{ij}(\alpha+1,\beta)\right)^2 / ((n)(n-1)) \end{bmatrix} \tag{1}$$

These features have already been calculated for you!! The file 'feat99.mat' in the ZIP file is a Matlab data file. It contains matrices **f2**, **f8**, and **f32** which contain the features calculated from each of the 16 blocks for all 10 images for n=2, 8, and 32 respectively. Each column in each matrix contains one sample

$$\begin{bmatrix} \underline{x}_{ij} \\ i \\ j \end{bmatrix} \tag{2}$$

To plot these features:

```
load feat99.mat
aplot(f2);
```

You will notice that the feature points are plotted using numbers 0-9. Each number corresponds to a different texture in the following order: cloth, cotton, grass, pigskin, wood, cork, paper, stone, raiffa, face. Sample image blocks for each texture are shown in Figure 1.

Keep in mind how our two features are defined in (1):

1. By looking at the images themselves, (e.g., on the SD372 home page), which do you think would be most likely to be confused with the other images? Why?
2. Which images are likely to be distinct? Why?

	Classified						
Truth	1	2	3	...	8	9	10
1	14	1	0	...	1	0	0
2	1	15	0	...	0	0	0
3	0	0	13	...	0	1	0
.	.	.	.	...	.	.	.
.	.	.	.	...	.	.	.
.	.	.	.	...	.	.	.
8	1	0	0	...	11	.	0
9	0	0	1	...	.	.	0
10	0	0	0	...	0	0	16

Table 1: Classification table. For this example, Image 1 was classified correctly fourteen times, classified incorrectly as Image 2 once, etc. Note that this is just an example, not necessarily what you should expect.

3 Labelled Classification

1. For each of the three feature matrices, use the MICD classification method to develop a classifier based on the data $\underline{x}_{ij}$. Do not try to plot the classification boundaries. Now, use your classifier to classify your data points.

2. What was the misclassification rate for each image and for each n? Use three tables, each like the one shown in Table 1, one table for each value of n, to compare how the images are classified correctly.

3. Compare and explain the results for different values of n.

4 Unlabelled Clustering

For this section we will treat the data points, $\underline{x}_{ij}$, as unlabelled points in feature space. Implement the K-means algorithm using the features in the **f32** matrix only.

1. Assume $K = 10$. Pick ten points randomly from your data $\underline{x}_{ij}$ and use these ten points as your initial prototypes.

2. Develop and apply the K-means algorithm using the selected prototypes. Plot the position of the 10 converged prototypes superimposed on the data $\underline{x}_{ij}$.

3. Repeat step 2 a few more times (with different, random initial prototypes each time). It is not necessary to submit any plots for these trials; however, compare the variability in the clustering from your trials. State your conclusions and observations.

5 Report

Include in your report:

- A brief introduction.
- Discussion of your implementations and results.
- Printouts of pertinent graphs (properly labelled).
- M-files for each section.
- Include responses to all questions.
- A brief summary of your results with conclusions.